

Fast Image Restoration Method Based on the Multi-Resolution Layer

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Abstract

When transmitted through a poor quality network or stored on an unstable storage media, block-based code images will experience the block loss. To restore damaged images suffering from block loss, Best Neighborhood Matching and Jump and Look-Around BNM provide the most effective image restoration. However, while BNM offers good restoration quality, it requires a large calculation time. By “JUMP” method, JLBNM can effectively shorten the computation time but this comes at the cost of a loss in quality. We have therefore proposed a new image inpainting technique that uses the Wavelet Domain to deliver fast computation time and high restoration quality – Wavelet Stage BNM. Our proposed reconstruction algorithm includes three optimization techniques – change of analytical domain, consideration of texture composition and a new decision-making mechanism: Directional Wavelet Weighted Method. Theoretical analysis and experimental results demonstrate our method delivered fast computation time and high restoration quality.

Key Words: Wavelet, Image Restoration, Wireless, BNM and WSBNM

1. Introduction

The main image encoding technologies used today divide the image into several image blocks then encode each individual work. The image data is therefore preserved in a block-based format. Existing image and video compression standards that use this approach include JPEG, MPEG and H.263 [1–4]. When the block encoded image data is stored on an unstable storage media or transmitted through a network experiencing interference, the loss of bit data may result in the loss of image blocks. In more severe cases, consecutive image blocks may be lost. To restore damaged images suffering from block loss, many researchers have proposed a variety of block restoration algorithms for damaged images. Known as error concealment algorithms, these methods intended to restore images rendered unusable by damage

or avoid the waste of bandwidth caused by the network's Automatic Retransmission Query mechanism. The objective was to make the repaired image acceptable or even indistinguishable to the human eye.

The error concealment algorithms can be roughly divided into two types: 1. Spatial Affinity Interpolation Method [5,6] using short-range data; 2. Block-wise Similarity Image Restoration Method [7–10] using the matching of long-range data. Here the first method looks at the effective data in the neighborhood of the loss image block. The dc and lowest frequency components of effective neighborhood data are used as a basis for the restoration of lost image block through interpolation. However, since this kind of spatial interpolation based image block restoration method tends to use the image's low frequency components as a reference, this often leads to poor image quality after restoration. As for the second block restoration method, it uses block similarity as a reference to search for a best match for the effective

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data among the other blocks in the image. This method solves the first method's problem with insufficiently detailed textures so has attracted a great deal of research interest. Among these are the block similarity based image block restoration methods proposed by David Zhang such as Best Neighborhood Matching (BNM) [8], Jump and Look Around BNM (JLBNM) [9] and Intelligent Two-Step BNM (ITSBNM) [10].

First, to find the best match from the neighboring image data, BNM must carry out a detailed step-by-step search of the entire target image. This search method ensures that the identified image blocks give the best possible match. At the same time, as this BNM method searches the entire image, it requires a lot of search and computation time. To solve the problem of high search and computation time, Zhang et al. proposed JLBNM algorithm while Xino et al. proposed ITSBNM algorithm. The key concept in these two repair algorithms was turning the original step-by-step search method into a two-step process: Browse Search and Fine Search. Browse search was used to find the district with the most similar texture blocks. Fine search was then applied to the best match block found during this similar district. This effectively reduced the search time for finding the best match for each missing block in the image. The biggest difference between the two repair methods was their approach to fine search, with ITSBNM using a two-stage Diamond Search to improve search efficiency. On the other hand, browse search might miss the location of the Best Match Block and use a Next Best Match Block for its image restoration process. This lowers the quality of the restored image and the impact on image quality is particularly obvious for longer browse distances. This means that there is a trade-off between image quality and computation time.

To take both restoration quality and computation time, we proposed a new repair method – Wavelet Stage Best Neighborhood Matching. The main techniques involved are: First, use of wavelet transform to convert the search domain to the spatial-frequency domain in order to reduce search times. Secondly, as the wavelet layers contain both the horizontal, vertical and perpendicular components, this can be analyzed to improve the image restoration quality [11]. Finally, a new repair decision-making algorithm was proposed – Directional Wavelet Weighted Method. This paper is divided into five sec-

tions. In Section 2, the theoretical basis of this paper is discussed. By combining these theories, we propose a new block repair method that we describe in Section 3. To prove that the proposed method can deliver both good image quality and reduce the search time, we tested our method with different images and compared them with existing image repair methods. The last section is the conclusion.

2. Previous Related Work

In order to acquire good repair results, damaged block reconstruction needs to address three primary areas of concern: 2.1 the analysis domain of the damaged image, 2.2 the block repairing reference data, and 2.3 the different directional texture estimate.

2.1 Discrete Wavelet Transform

The discrete wavelet transform (DWT) is widely applied for image compression, primarily because the wavelet transform has the spatial-frequency domain relativity at the same time. In DWT, with respect to the spatial domain $V_j + 1$, the function $f(x)$ can be expressed as the base expansion of the layer 1 spatial domain, analyzed as Eq. (1):

$$f(x) = \sum_k c_{j,k} \phi_{j,k}(x) + \sum_{j=0}^J d_{j,k} \psi_{j,k}(x) \quad j, k \in \mathbb{Z} \quad (1)$$

where $\phi_{j,k}$ and $\psi_{j,k}$ represent the scaling function and the wavelet function respectively, and satisfy the following two Eqs. (2) and (3):

$$\phi_{j,k}(x) = 2^{j/2} \phi(2^j x - k) \quad j, k \in \mathbb{Z} \quad (2)$$

$$\psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k) \quad j, k \in \mathbb{Z} \quad (3)$$

where $c_{j,k}$ and $d_{j,k}$ represent the expansion coefficients of V_j and W_j spatial domains respectively, and can be evaluated by the following two equations:

$$c_{j,k} = \sum_n c_{j+1,n} h(n-2k) \quad j, k \in \mathbb{Z} \quad (4)$$

$$d_{j,k} = \sum_n c_{j+1,n} g(n-2k) \quad j, k \in \mathbb{Z} \quad (5)$$

where $h(n)$ and $g(n)$ are called scaling coefficients and

wavelet coefficients respectively. By observing Eq. (4) and Eq. (5), coefficient $c_{j,k}$ is evaluated based on the coefficients of $c_{j+1,k}$ from a prior layer in the spatial domain and the scaling coefficient $h(n)$ after the execution of the folding evaluation and the decreasing of the sampling rate by 2. Similarly, coefficient $d_{j,k}$ is evaluated based on the coefficients of $c_{j+1,k}$ from a prior layer in the spatial domains and the wavelet coefficient $g(n)$ after the execution of the folding evaluation and the decreasing of the sampling rate by 2. This is the reason that WT and the wave-filtering theory can be combined [8].

The original image was processed through a secondary-level WT, as illustrated in Figure 1(c), where the highlighted image in the uppermost left hand corner is represented by the section LL_2 illustrated in Figure 1(d). Where analysis is concerned, the components of the overall image composition are all taken into consideration. This procedure can also be utilized as preliminary image analysis. Then the four components LL_2 , LH_2 , LH_2 , and HH_2 are then processed through reversed WT to heighten the resolution of the image as shown in Figure 1(a), where the highlighted image in the upper left hand corner is represented by the section LL_1 illustrated in Figure 1(b). This would result in the increasing of frequency components within the image, which would then contribute towards the depiction of local area textural features.

Additionally, since the analytical domain possesses spatial-frequency relationship after image is subjected to DWT transform, this forms a spatial-frequency relational pyramid. This means that each location on the image has its own corresponding wavelet layers of different frequencies. The best similar search method can therefore use this characteristic of DWT to move gradually layer-by-layer from the lowest frequency analytical layer to the highest frequency analytical layer in a progressive search. Since the search area gradually narrows from overall image components to local regional components as the wavelet analysis layer is gradually increased, this can effectively save a great deal of search and calculation time as suggested by Do et al. [12].

2.2 BNM

To search for the best similar image block to repair a damaged image, Zhang [8,9,13] proposed two different repair algorithms including BNM and JLBNM. The main

concept of these methods is they consider the width of one pixel of neighboring information $x_{i+m,j+n}$ surrounding the damaged block. Moreover, these methods use neighborhood pixel information through the 1-order matching function $v(z)$, as Eq. (6), to transform that will compare with the same size blocks within the searching range block. Through block comparison continuously, the best neighborhood matching block will obtain the minimum MSE_M by Eq. (7).

$$v(x) = a_0 + a_1 x \quad (6)$$

$$a_1 = \frac{n_M \cdot \sum m \cdot x_d \cdot x_r - \sum m \cdot x_d - \sum m \cdot x_r}{n_M \cdot \sum m \cdot x_r^2 - (\sum m \cdot x_r)^2}$$

$$a_0 = \frac{1}{n_M} [\sum m \cdot x_d - a_1 \cdot \sum m \cdot x_r]$$

$$MSE_M = \frac{1}{n_M} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} (1 - f_{k+m,l+n}) \cdot (v(x_{i+m,j+n}) - x_{k+m,l+n}) \quad (7)$$

$$m = 1 - f_{k+m,l+n}$$

$$x_d = x_{k+m,j+n}$$

$$x_r = x_{i+m,j+n}$$

where $v(x)$ is the 1-order matching function used to convert the neighboring information of the damage block x_d , a_1 is first order conversion coefficient of the 1-order matching function, a_0 is the zeroth order conversion coefficient of the 1-order matching function, x_r is the range block on the searching range block, x_d is the neighborhood information of the damaged block, and m is the mark of the useful pixel value, $f_{k+m,l+n}$ is a binary flag indicating whether the image is lost or not. If it is lost, $f_{i,j} = 1$, otherwise $f_{i,j} = 0$. The relation of the block matching method is shown in Figure 2. Although this algorithm can be used to find the best neighborhood matching block, this way requires high computation overhead

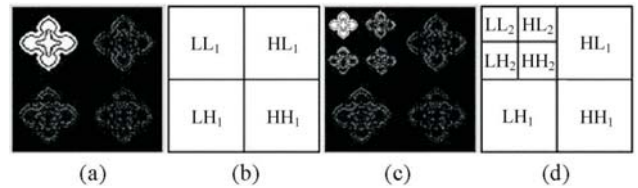


Figure 1. Results of the WT derived from various layers of a given image (a) 1-Level DWT image, (b) 1-Level DWT Resolution, (c) 2-Level DWT image, (d) 2-Level DWT Resolution.

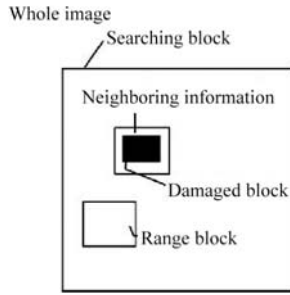


Figure 2. Structure of damaged block, range block, searching block, and neighboring information with default sizes.

to search for similar blocks. The JLBNM algorithm is to solve the problem of great computation overhead due to using the jump and look around method for reducing the searching range. “Jump stage” is used as the browse search, and “Look around” is used as the fine search. By reducing the search range, search time is reduced as well. The concept of ITSBNM algorithm resemble JLBNM algorithm, but the biggest differentia is using the diamond search in fine search. However, these ways will sacrifice the quality of the reconstructed image in exchange for lower computational overhead. In order to resolve this problem, we propose a new BNM algorithm that considers both low computation overhead and high repair quality. Its main idea is to search the best neighborhood matching from the eight neighboring blocks on the wavelet domain.

2.3 Directional Texture Reconstruction

In section 2.1, we discussed the characteristic of the wavelet transform that has the relativity of the spatial composition and the frequency composition. On the different wavelet layer (different frequency band), each band includes the three directional wavelet coefficients of vertical direction, horizontal direction, and diagonal direction. Therefore, Rane [7] uses this characteristic to implement the wavelet-domain reconstruction of lost blocks in wireless image transmission and packet-switched networks. The reconstruction method of lost blocks includes the following steps: 1. classify lost blocks into “edgy” and “non-edgy”, 2. reconstruct edgy blocks from selected edgy blocks in the 8-neighborhood and non-edgy blocks from selected non-edgy blocks in the 8-neighborhood.

For the reconstruction of edgy blocks, the algo-

rithm has two steps: 1. the type of detail (vertical and horizontal) being reconstructed determines which of the neighboring blocks are used for reconstruction; 2. the above propagation of details does not cross an edge. To fill in the wavelet coefficients on the damaged block, this method uses the interpolation function in a different direction, as shown in Eq. (8). The minimum of the mean square error provides smooth transition, as shown in Eq. (9).

$$v(x) = w_{D1} \cdot x_{D1} + w_{D2} \cdot x_{D2} \quad (8)$$

$$MSE_M = \frac{1}{N \times N} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} (1 - f_{k+m,l+n}) (v(x_{i+m,j+n}) - x_{k+m,l+n})^2 \quad (9)$$

where w_{D1} and w_{D2} are weighted values to represent the contribution degree of neighboring blocks x_{D1} and x_{D2} respectively. If repairing image on the vertical direction, w_{D1} represents the upper neighboring block of $x_{i+m,j+n}$ and w_{D2} represents the lower neighboring block of $x_{i+m,j+n}$. If the x_{D1} nears to $x_{i+m,j+n}$, the w_{D1} takes the bigger weighted value, otherwise the w_{D2} takes the bigger one. The total weighted value of w_{D1} and w_{D2} equals 1. Although this method considers three directive veins, if the neighborhood block has complicated veins at the same time then this method cannot reconstruct the correct veins. In order to resolve this problem, we propose the novel directional texture reconstruction method that considers the vein intensity of the neighboring coefficient around the damaged block to determine the weighted value. This called the directional wavelet weight method (DWWM) and is discussed in the next section. A simple experiment explains the problem of the Rane’s method, as shown in Figure 3.

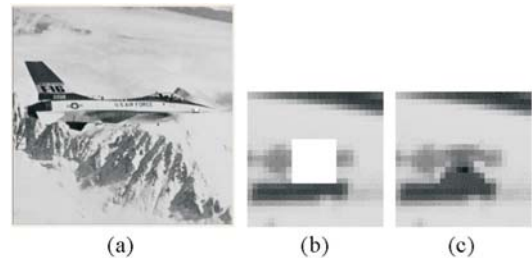


Figure 3. The simple experiment to find the Rane’s repair problem: (a) Damaged image, (b) Zoom-in damaged area, (c) Rane’s method.

3. Proposed Algorithm

According to the results of the three major steps of the previous related work discussed above, this section concentrates on the integration of these steps and proposes Wavelet Stage Best Neighborhood Matching (WSBNM), to consider the different spatial-frequency composition and the different directional texture composition at the same time to carry out the image reconstruction.

3.1 Details of WSBNM

In this section, the proposed method uses the wavelet characteristic with multi-frequency bands to carry out the frequency composition repair on different wavelet layers separately. By searching upwards from “low frequency wavelet layers” to the “high frequency wavelet layers” for the best matching block, this will achieve the goal of shortening “computation time”. The main idea of the repair image on the wavelet domain is from the method of Rane [14]. But its algorithm, in addition to handling complexity (classify) and in the wavelet coefficients decision, includes the two serious conditions for mistake repair and insufficient information. The Rane’s method did not consider the direction of the neighboring texture and the weighted value. It extended three directional wavelet coefficients directly rather than considered the relative texture of directive wavelet coefficients. The proposed method is to resolve the complicated classification problem of lost blocks, and it uses the weighted value of the neighborhood wavelet coefficients at each wavelet layer to replace the lost block classification. According to the different wavelet layers, we depend on the wavelet coefficients of the different layers multiplied by the different weight value, and thus refer to it as DWWM. This formula is shown as Eqs. (10)–(14) and the relations of each wavelet layer multiply the weighted value to estimate the vein direction of the damaged block, the positions of the different directional weighted values are shown in Figure 4.

$$vwv = 4 \times abs(vc_3) + 2 \times abs(vc_2) + 1 \times abs(vc_1) \quad (10)$$

$$hwv = 4 \times abs(hc_3) + 2 \times abs(hc_2) + 1 \times abs(hc_1) \quad (11)$$

$$d1wv = 4 \times abs(d1c_3) + 2 \times abs(d1c_2) + 1 \times abs(d1c_1) \quad (12)$$

$$d2wv = 4 \times abs(d2c_3) + 2 \times abs(d2c_2) + 1 \times abs(d2c_1) \quad (13)$$

$$twv = vwv + hwv + d1wv + d2wv \quad (14)$$

where vwv , hwv , $d1wv$, and $d2wv$ are the absolute weighted values of the neighborhood block of the vertical, horizontal, left-top diagonal, and right-top diagonal separately; hc_n , vc_n , $d1c_n$, and $d2c_n$ are the wavelet coefficients of the neighborhood block of the vertical, horizontal, left-top diagonal, and right-top diagonal separately; and twv is the total weighted value. The related position of these coefficients is shown in Figure 5.

When the repair procedure needs to obtain the contribution of the directional vein compositions, the significance of the four directional wavelet coefficients are calculated via each directional weighted value divided by the total weighted value (twv) separately. If this method did not consider these proportions of the directive information using the Rane’s method, the repaired image would have vein mistakes, as shown in Figure 6. In Figure 6(c), we

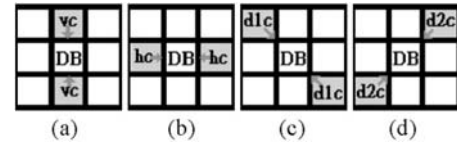


Figure 4. The relation of each directional neighboring coefficient to repair the damaged coefficients on the damaged block: (a)Vertical, (b)Horizontal, (c)Left-top diagonal, (d)Right-top diagonal.

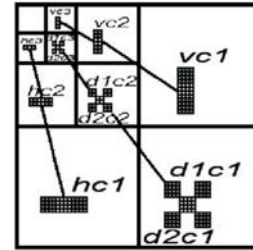


Figure 5. The related position of the wavelet coefficients in the directive veins.

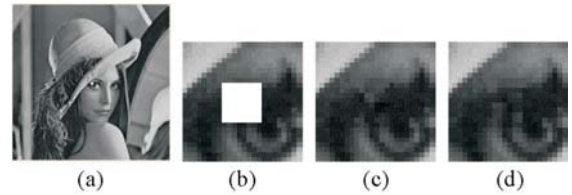


Figure 6. Compare the repair results in terms of the directional information: (a)Damaged image, (b)Zoom-in damaged area, (c)Direct method, (d)Consider directional weighted value.

can clearly find two problems that include inconsistencies around the eyes and the eyeball is out of shape.

After predicting the wavelet coefficients of the damaged block for different directional texture information, although this method can acquire the vein images through the inverse wavelet transform, the repaired image will probably lead to the block effect, as shown in Figure 7(b). In order to resolve this problem, we propose the adjustable block consecution method that is based on the concept that continuous blocks have the same pixel values. The main idea for this comes from the fractal geometry concept of searching for similar blocks to carry out the image compression. The adjustable block equation is shown in Eq. (15) and the estimate equation for the best neighborhood matching is shown in Eq. (16).

$$v(x) = g \cdot x + s \quad (15)$$

$$MSE_M = \frac{1}{N \times N} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} (1 - f_{k+m,l+n})(v(x_{i+m,j+n}) - x_{k+m,l+n})^2 \quad (16)$$

where $x_{i+m,j+n}$ is the damaged block, $v(x)$ is the adjusted block through the pixel value shifting S , and the gradient adjustment g and $x_{k+m,l+n}$ are the neighboring block for most similar searching. When the equation acquires the minimum value, it means the adjusted block obtains the best adjustment to connect the neighborhood blocks, as shown in Figure 7(c). Through the adjustment method, the repaired image can avoid visual discomfort.

3.2 Flow Chart of the Proposed Algorithm

Until now, we have been describing the utilization of various types of spatial-frequency analysis using DWT as a foundation, using DWWM to analyze various neighboring block features of the damaged block in different wavelet layers, and predicting the wavelet coefficients of the damaged block in order to reach the goal of multi-

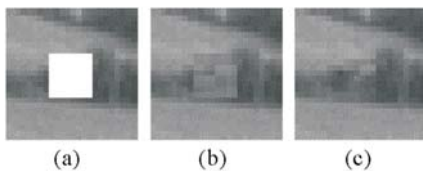


Figure 7. The visual adjustment to solve the block effect of the reconstructed image: (a) Damaged block, (b) parameters not adjusted, (c) Adjusted parameters.

directional block repairing. Summarizing the overall execution process for the WSBNM of improving the current BNM techniques, Figure 8 illustrates the flow chart that accompanies the detailed processing steps.

Step 1. Establishing the foundation for multi-resolution image analysis

The first step of this image inpainting method is to analyze the various resolutions of an image by utilizing DWT. The main reason for addressing the third-stage wavelet transform in this paper is to separate the original image into several different sets of image frequencies. These include different frequency layers. The main reason is to consider the image compression standard that carries out the block size of 8×8 . By utilizing the horizontal, vertical and diagonal components of each individual frequency layer, it is similar to the natural human repairing method from coarse part to fine part for further block repairing.

Step 2. Determining on the weighted value of the neighboring block for modifying the adjacent image blocks (DWWM)

Manipulation of the corresponding LH, HL and HH wavelet coefficients of the repairing block pixels should be done prior to the execution of filling in the directional wavelet coefficients. After determining identity of the proper values of the LH, HL and HH wavelet coefficients, a correct directional veins coefficients of the damaged block will be estimated.

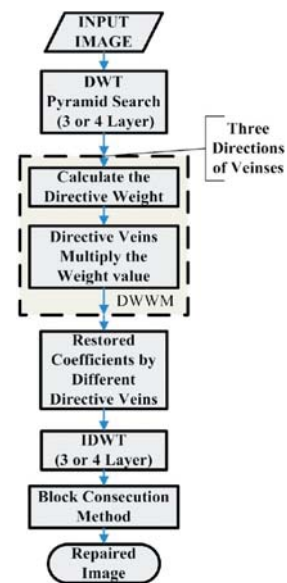


Figure 8. Flowchart of the WSBNM.

Step 3. Filling in the different layer coefficients for an optimized directional reconstruction (DWWM)

Recalling the concepts mentioned in section 2.3 that in advance target an optimized directive coefficient with the DWWM, the contribution of the different directive-frequency coefficient estimate should be considered. Thus an optimized similar vein coefficient is found and used to fill in the damaged block on each wavelet layer.

Step 4. Executing the inverse wavelet transform to acquire the reconstructed image

Manipulation of the corresponding LH, HL and HH wavelet coefficients of the inpainting pixels should be done prior to the execution of the inverse WT for restoring the whole image. Because this method considers the different directions and frequencies of wavelet coefficient veins, the repaired image from the inverse wavelet transform will include the correct veins in the reconstructed image.

Step 5. Executing the detail adjustment to reduce the block effect

The repaired image from the reconstructed wavelet coefficients obtains the estimated texture from the neighboring block, but the repaired block maybe lead to block effect with neighborhood blocks. In order to obtain good visual observation results, the final step of WSBNM is using the formula to carry out the adjusting work. Therefore the proposed method obtains the good visual repairing result and on the MSE value.

4. Experimental Results

To demonstrate that the proposed method provides the most effective repair results, two major experimental processes were conducted. First, Section 4.1 shows a comparison of image repair results with the existing Rane's method, BNM, JLBNM, and ITSBNM methods. Then, Section 4.2 shows how several characteristic images were repaired to demonstrate the usefulness of the proposed method for an arbitrary image.

4.1 Comparison of Image Repairing Results with the Best Existing Methods

In wireless transmission, the image is divided into blocks for transmission over a wireless channel. To consider different conditions, we have assumed that (1) the

damaged image includes the lost block (8×8 and 16×16 pixels) and (2) continuous lost blocks (lines losses) that conform to the JPEG compression standard. In first experiment, we consider only damaged block (8×8 pixels) condition to carry out the repair test. The random block loss rates are arranged from 2.5% to 15%. These experimental results are separated into two groups. In the first group, repair results from the proposed method are compared with those from the existing Rane's method, BNM, JLBNM, and ITSBNM methods for different block loss rates. In Figure 9, the repair results of Goldhill show that the proposed method has higher PSNR and better visual result than the existing method clearly. The main reason for this is that is our method not only considers more reference information carried on the image repair estimate, but also considers the multi-directional veins extension. The comparisons of the restoration results of the different images by the repaired methods mentioned above are illustrated in Figures 10–12. The repaired results of the proposed method are obviously better than others.

In the second group, the experiments compare the restoration time of the different repair methods. In Figure 13, it is clear that the proposed method's computational overhead is lower than that of the BNM and JLBNM. The main reason is that BNM must spend a large amount

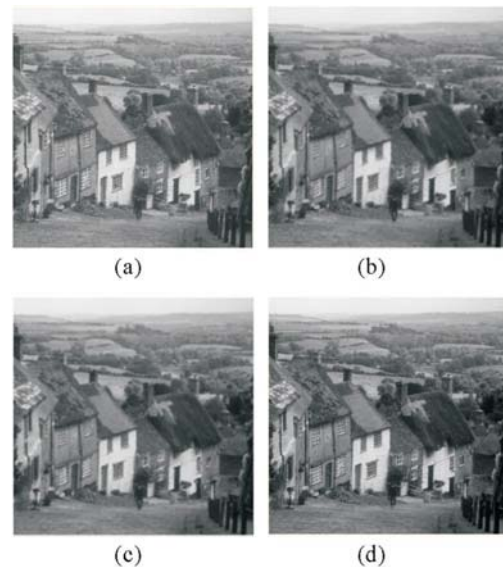


Figure 9. The reconstructed results for “Goldhill” with block loss rate 10%. Block size is 8×8 . (a) Restored image by Rane's method, PSNR = 35.00, (b) Restored image by BNM, PSNR = 35.28, (c) Restored image by JLBNM, PSNR = 34.83, (d) Restored image by WSBNM, PSNR = 36.33.

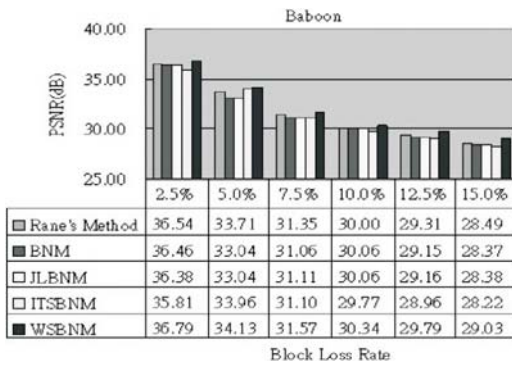


Figure 10. Comparison of repair results of the PSNR for “Baboon” achieved by Rane’s method, BNM, JBNM, ITSBNM, and WSBNM.

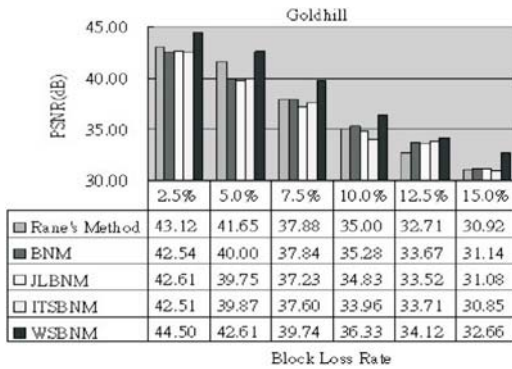


Figure 11. Comparison of repair results of the PSNR for “Goldhill” achieved by Rane’s method, BNM, JBNM, ITSBNM, and WSBNM.

of searching time to carry out the best neighborhood matching. Although the JLBNM uses the technique of the browse search and fine search to reduce the computation time, this method still needs some time to carry on the image matching, and it loses part of the reconstruction quality. Therefore the proposed method not only does not need spend time for searching the BNM but also uses the wavelet domain characteristics, including the multi-frequency resolution and multi-direction to immediately carry out the image repair. So the proposed method can provide better reconstruction quality and requires less computational overhead.

Secondary, to demonstrate that the proposed method can satisfy another image compression standard. The testing block size from 8×8 pixels is changed to 16×16 pixels for the testing experiments. And the experimental results of a different methods are shown in Figure 14.

Finally, in wireless transmissions, other conditions of the transmission error can cause entire sections to become

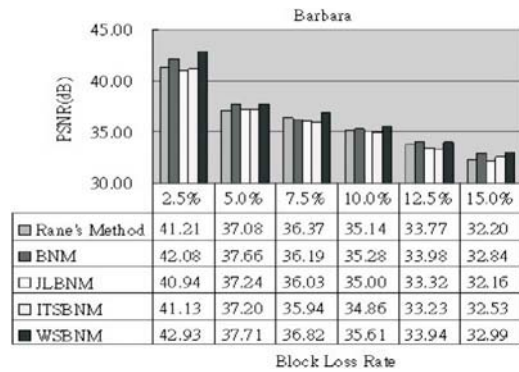


Figure 12. Comparison of repair results of the PSNR for “Barbara” achieved by Rane’s method, BNM, JBNM, ITSBNM, and WSBNM.

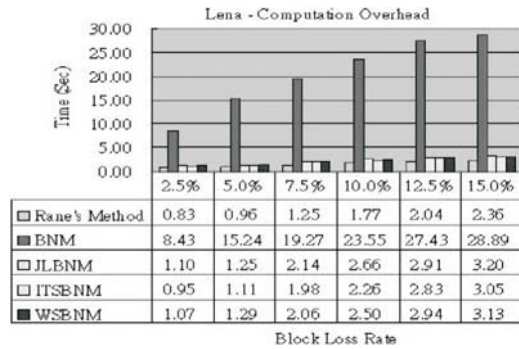


Figure 13. Comparison repair results of the processing time for “Lena” achieved by Rane’s method, BNM, JBNM, ITSBNM, and WSBNM.

damaged due to losing a sequence of lost blocks. Figure 15 shows the repaired results of different methods.

4.2 Results of the Image Repair on an Arbitrary Image

In this section, in order to prove the usefulness of the proposed method for normal images, three different images were chosen as test images. The damage conditions include a single damaged block, the consecutive blocks, and a missing line. The total destroy rate in each test image be up to 15%. The testing images include the repeated stripe pattern image, scenery image, and portrait image for testing. The reconstructed results are separated in Figures 16–17. These images even have the complicated image veins, but this method can still rebuild a good image.

5. Conclusion

A novel algorithm based on the wavelet transform to repair the block lost image was presented. This method is

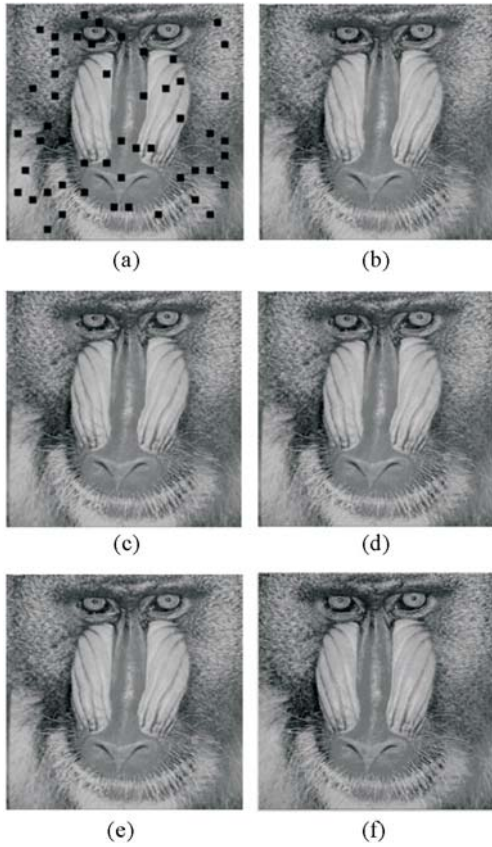


Figure 14. Restoration results for “Baboon” with block loss rate of 5% and block size is 16×16 . (a) Damaged image, (b) Restore by Rane’s method PSNR = 31.23, (c) Restore by BNM. PSNR = 31.40, (d) Restore by JLBNM. PSNR = 31.15, (e) Restore by ITSBNM PSNR = 31.18, (f) Restore by WSBNM. PSNR = 31.46.



Figure 15. Restoration results for “Barbara” with three whole lines losses. Block size is 16×16 . (a) Damaged image, (b) Restore by Rane’s method. PSNR = 30.08, (c) Restore by BNM. PSNR = 30.45, (d) Restore by JLBNM. PSNR = 30.25, (e) Restore by ITSBNM. PSNR = 30.68, (f) Restore by WSBNM. PSNR = 31.12.

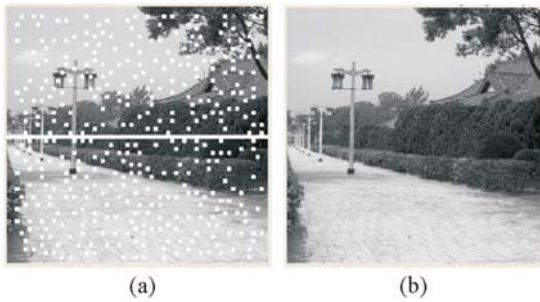


Figure 16. Restored results for “scenery” with the three kinds of damage conditions and damage rate is 15%. Block size is 8×8 : (a) Damaged image, (b) Restored image by WSBNM. PSNR = 32.11.

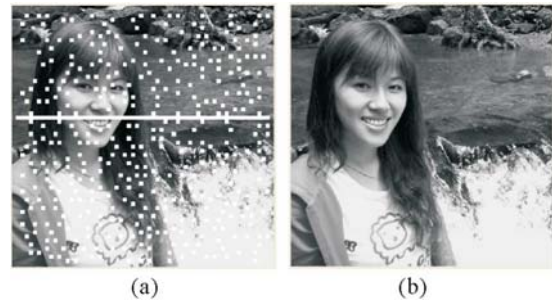


Figure 17. Restored results for “portrait” with the three kinds of damage conditions and damage rate is 15%. Block size is 8×8 : (a) Damaged image, (b) Restored image by WSBNM. PSNR = 33.97.

combined with the best neighborhood matching approach and the different-frequency repair on wavelet domain to carry on the fast lost block reconstruction. Thus, the repair image is separated into the different wavelet

layers to carry out texture reconstruction and acquire the estimate of the best veins. The experimental results indicate that this algorithm provides significant improvement over existing algorithms in terms of both subjective

and objective evaluations. The method considers the relationship between the different frequency compositions and each layer's neighboring texture relations at the same time. However, it does not need to use a long-range correlation to find the best neighborhood matching in the big search domain, to thereby spend a lot of calculation time. Another significant advantage of the method is that the image wavelet dimension not only resolves the different frequency compositions but also provides three directive compositions, and so it is advantageous to repair the fast and right veins through the WSBNM algorithm.

Although the WSBNM provides better repair result than Rane's method, BNM, JLBNM, and ITSBNM methods, its image repair result still did not attain perfection by simple directive estimate method. In future research we will try to research the better directive veins estimate method to improve the repairing quality of the damage image.

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